

# IoT and Deep Learning based Agri 4.0 practices for Sustainable Farming

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**Abstract**—The agricultural sector must adjust to the shifting environmental conditions and adopt Agriculture Industry 4.0 (Agri 4.0) technologies to increase productivity in order to meet the food demands of a growing population. Integration of the Internet of Things (IoT) and Deep Learning (DL) in the context of Agri 4.0 is a promising approach to addressing the pressing challenges facing existing farming practices. The implementation of this approach has the capability to transform agriculture into a sustainable enterprise capable of meeting the increasing demands of a rapidly changing world. Agri 4.0 applications, coupled with IoT and DL models, may provide a way to do it. In this article, current adaptation challenges and the state-of-the-art in Agri 4.0 are addressed. The areas of focus include timely intervention in environmental control using IoT to collect and analyze various environmental factors. This data can then be used to automate farm management and DL-based image processing using advanced neural networks for the detection of plant diseases, pests, and weeds, as well as for transparent agri-product grading. Besides, there are still some challenges in bringing such technologies to implementation in the small-scale agri-sector. However, this article demonstrates how the integration of these technologies in the Industry 4.0-based agriculture sector can transform it into a sustainable agro-industry.

**Keywords**—IoT, Deep Learning, Agri 4.0, Sustainable farming

## I. INTRODUCTION (HEADING 1)

Agriculture plays a crucial role in feeding the world's population and requires sustainable practices. Agri 4.0 offers an innovative solution to keep up with the population explosion and urbanization. Adopting Agri 4.0 benefits both farmers and the environment by improving yields and reducing resource usage, while also supporting conservation and reduced environmental impact. The Agri 4.0 industrial revolution integrates digital technologies for sustainable farming practices, such as precision agriculture, AI, and data analytics, which are just some of the ways in which technology is being used to improve sustainability in farming.

The use of drones and IoT sensors provides targeted applications and monitors the use of resources, helping farmers make informed decisions. In comparison to current farming practices, Agri 4.0 is essential for the future of agriculture and offers a promising solution. By embracing this approach, farmers can improve their yields and reduce waste, ultimately benefiting both their bottom line and the environment. They can also contribute to a sustainable future and meet the world's growing food needs.

## II. AGRICULTURE 4.0 – NEED OF THE HOUR

Despite the fact that agriculture has been impacted by every industrial revolution, today the agricultural sector is experiencing a new revolution, called Agriculture 4.0, with the use of "Industry 4.0" digital technologies [1]. The term "Agri 4.0" refers to the convergence of precision agriculture and information and communication technology (ICT) [2]. The need for Agri 4.0 is more pressing now than ever, with the increasing demand for food due to the increasing world population, shifting climatic trends, and unexpected weather events being major factors that have impacted agricultural production. Agri 4.0 is process of upgrading the existing agri-system through intelligence and the use of cross-industrial technology and applications [3]. Data-driven technology has the potential to bring about positive implications for global farming through Agri 4.0. The utilization of this technology can result in heightened productivity, increased efficiency, and more environmentally-friendly practices. Furthermore, it can support informed decision making and bridge the rural-urban divide, contributing to the overall growth and sustainability of the agriculture industry.

In India, Agri 4.0 is a critical priority for several reasons. Firstly, India is projected to become the world's most populous country by the end of this decade, according to the United Nations' World Population Prospects 2022 top ten countries ranking. With a projected increase from 1,412 million in 2022 to 1,668 million by 2050 [4], the country is facing a rising demand for food and other farm products. Secondly, The World Bank's World Development Indicators [5] indicate that India has been experiencing a reduction in arable land, as shown in Fig. 1, for several decades due to urbanization, industrialization, and climate change. This

decline has resulted in several issues for the Indian agriculture sector, such as declining crop yields, soil degradation, and biodiversity loss. Climate change has worsened this problem, causing extreme weather events and irregular rainfall patterns that affect crop output. Fig. 2 shows the percentage of agricultural land worldwide.

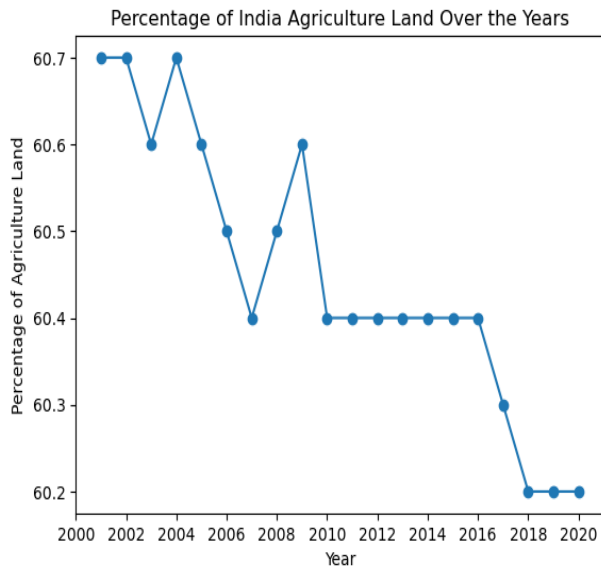


FIGURE 1. Percentage of Agriculture Land in India [5]

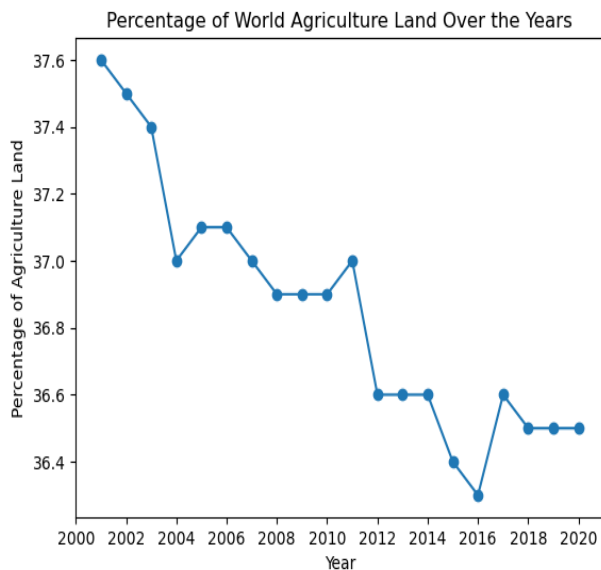


FIGURE 2. Percentage of Agriculture Land in World [5]

Lastly, there is a reduction of agricultural labor and related workers, as there aren't enough opportunities for daily wages outside of the planting and harvesting seasons. People often migrate in search of better opportunities, and rural-urban and interstate migration has increased significantly over the last ten years, according to the International Labor organization as shown in Fig.3 [6]. As a result of this migration, the availability of labor for agriculture has decreased, causing a labor shortage in the sector. This labor shortage has led to various issues, including decreased productivity, rising wages, and increased reliance on migrant labor. To address

these challenges, it is essential to adopt modern technologies and data-driven solutions that can help farmers maximize their productivity and improve efficiency.

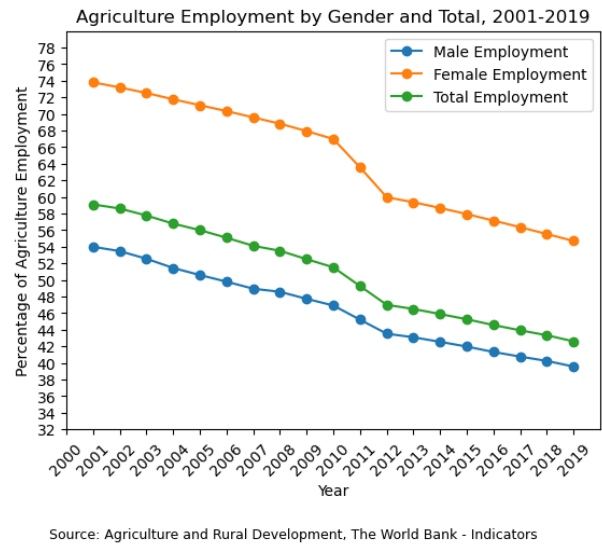


FIGURE 3. Percentage of Agriculture Employment in India [6]

### III. CHALLENGES IN ADOPTING AGRI 4.0

Implementing Agri 4.0, a modern agricultural approach relying on data, faces several difficulties globally. Developing nations frequently struggle with inadequate infrastructure that impedes the integration of these technologies. Furthermore, small farmers may struggle to pay for the required technology. To utilize Agri 4.0 effectively, farmers need to be trained and have the necessary technical skills. Ensuring the privacy and security of farmers' data is also a concern that needs to be addressed. In order for Agri 4.0 to be widely adopted, a clear and well-defined regulatory framework must be established. Overcoming these challenges will play a critical role in the successful implementation of Agri 4.0 on a global scale.

A lack of education, awareness, finance, technical assistance, and infrastructure has been the main obstacle to implementing Agri 4.0 in India. One of the major obstacles to its adoption is the fact that farmers are not educated about or aware of Agri 4.0. This ignorance leads to reluctance among many farmers to adopt the latest agricultural advancements and technologies. Additionally, farmers lack the necessary resources to invest in these technologies due to a lack of finance and technical support. The absence of infrastructure in India's rural areas, such as electricity and internet connectivity, further hampers the adoption of Agri 4.0. Despite most farmers practicing agriculture on a small scale and lacking the resources to collaborate properly and adopt Agri 4.0 technologies, the lack of organization among farmers is also a problem. Authorities and stakeholders must build infrastructure, provide access to finance and technical assistance, and develop education and training programs to address these issues. They must also promote and reward farmer cooperation to spread the adoption of Agri 4.0, resulting in sustainable and successful agricultural practices.

#### IV. STATE OF THE ART IN AGRI 4.0

Agri-4.0 brings a new level of precision, efficiency and sustainability to the agriculture sector. The possibilities of Agri-4.0 are extensive, ranging from the use of precision agriculture to improve crop yields and reduce waste, to the use of digital agriculture and IoT devices to optimize crop management and decision-making. In terms of crop types, Agri-4.0 can be applied to a wide range of crops, including rice, wheat, fruits, and vegetables, to improve yields, conserve resources, and reduce waste.

Sustainability models for Agri-4.0 are also being developed, with a focus on reducing waste, conserving resources, and improving soil health. In India and globally, models of sustainability for both generic and crop-specific types are being explored, with an emphasis on creating closed-loop systems that conserve resources and reduce waste. For example, precision agriculture techniques [7, 8] can be used to manage water and nutrient resources, while renewable energy sources and waste-to-energy systems can help to reduce greenhouse gas emissions [9]. It's transforming the way crops are grown, harvested, and distributed, creating more efficient and sustainable agricultural systems that meet the needs of both farmers and consumers.

#### V. INTERNET OF THINGS IN AGRI 4.0

The Internet of Things (IoT) has a substantial impact on agriculture, which is often referred to as "Agri 4.0." IoT technologies enable farmers to gather data from various sources [10]. They can improve their farming operations by employing this information. IoT's impact on agriculture not only increases efficiency but also helps farmers make more sustainable decisions to protect the environment. With the help of IoT, agriculture is becoming more data-driven, intelligent, and productive. Generic models of IoT in Agri 4.0 are intended to be adaptable across a wide range of agricultural applications, including wireless sensor networks, precision agriculture, animal monitoring, and supply chain management.

In the wireless sensor network model [11, 12], a network of wireless sensors is set up to collect information on environmental factors including temperature, humidity, and soil moisture. The application of fertilizer, irrigation, and pest control can all be optimized using this data. The concept of precision agriculture entails the use of sensors and other IoT devices to collect data on crop health, soil conditions, and weather patterns in order to influence decisions about planting, harvesting, and other elements of crop management. Using IoT devices, the supply chain management model tracks the movement of goods and products along the agricultural supply chain from the farm to the point of sale. These are the generic models that provide a framework for incorporating IoT into agriculture 4.0 [13], but these models may need to be adapted or combined with other technologies to meet the specific requirements of different crops and farming practices.

#### VI. DEEP LEARNING IN AGRI 4.0

Deep learning (DL) is transforming agriculture by providing farmers with unprecedented levels of precision and

efficiency. Because of its ability to analyse massive amounts of data, DL is assisting farmers in streamlining their operations and making sound decisions. DL is helping farmers raise their yields, cut costs, and make better use of their resources by doing everything from forecasting crop harvests to identifying pests and diseases. In short, DL techniques are making agriculture more data-driven, efficient, and sustainable, thereby ensuring food production's future. DL [14] is a rapidly growing field, with numerous applications in the farming industry. Most popular and commonly used techniques are Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) [15]. These neural networks are used to make more informed decisions, improve efficiency, and increase yields. DL models are designed to cater to the specific needs of different crops. These models employ advanced algorithms to analyze data collected from various sources, such as sensors, drones, and satellites.

For instance, Artificial Neural Networks (ANNs) are widely used for crop yield prediction, where the technology analyses past data such as weather patterns, soil moisture levels, and fertilizer usage to anticipate crop yields accurately. Another application is in precision agriculture, where ANNs are used to optimize drip irrigation systems [16]. Convolutional Neural Networks (CNNs) can process satellite images to predict drought [17] and drone imagery helps us to map fields and monitor crop growth patterns, providing valuable insights into crop health and yield potential [18]. Additionally, these CNNs can also be trained to analyse images taken by infrared cameras, providing a non-invasive means of monitoring plant temperature [19], which can be an indicator of water stress and disease. Recurrent Neural Networks (RNNs) have the ability to handle time-series data, such as weather patterns and crop growth stages, which makes them ideal for predicting future crop yields and weather patterns [20]. RNNs have also been integrated into smart irrigation systems with Long Short-Term Memory (LSTM) [21], which use soil moisture level data to optimise watering schedules.

#### VII. FOCUS AREA OF RESEARCH

##### A. *Environmental Monitoring based on timely intervention.*

Environmental management based on timely intervention, utilising IoT in Agri 4.0, entails capturing real-time data from sensors and acting on that data. The sensors can be positioned in a multitude of locations, including a field, greenhouse, or storage facility, and they can track variables including temperature, humidity, soil moisture, light intensity, and CO2 levels. These sensors gather data, which is then sent to a central system where it may be analysed and used to make informed decisions. In case of timely intervention, the data is rapidly analysed, and action is taken to prevent or reduce the impact of bad environmental conditions on crops. For example, if sensors detect that the temperature in a greenhouse is rising, the system can automatically engage the ventilation system or a watering system to reduce the temperature. This intervention is timely since it occurs shortly after the data is processed, lowering the likelihood of crop damage or loss.

A low-cost IoT platform for real-time greenhouse environment monitoring, created with an emphasis on Agriculture 4.0, is presented as a prototype in the article [22]. The platform was designed with the capacity to collect data on environmental elements such as temperature, humidity, sun radiation, air velocity, and CO<sub>2</sub> concentration and send it to external devices using wired and wireless connections.

An inexpensive technology for maximizing fertilizer dosage using intelligent fertigation pipelines is discussed in the article [23]. The system makes use of sensor networks, wireless technology, and data-processing circuit boards to help crops and to accomplish precision farming. Four distinct dosage methods, which have been tested with various granular and liquid fertilizers, are included in the system. Accurate modelling enables exact control of the dosing systems. The system's findings enable the fertilizer dose to be optimized, which lowers production costs, improves environmental sustainability, and optimizes production in terms of quantity and quality.

### *B. Automation Management*

The integration of IoT and Agri 4.0 for automation management in agriculture has brought significant advancements in farming practices. IoT devices and sensors can collect and transmit data from the field, allowing farmers to monitor crop growth, soil moisture levels, temperature, and other environmental conditions. The data collected can be analysed in real-time, providing farmers with valuable insights into their operations, allowing them to make informed decisions that can optimize crop yield and reduce costs. This technology also enables farmers to automate various processes such as irrigation, fertilization, and pest control, eliminating the need for manual labour and reducing the risk of human error.

Agri 4.0 encompasses various technological advancements, including precision agriculture, which uses data from IoT devices to analyse soil and plant health, guiding farmers to make better decisions about the use of water, fertilizers, and other inputs. The development of automated irrigation system leverages IoT devices to aid farmers in India. The system is designed to be low-cost and user-friendly, utilising an Arduino Uno, GSM module, an Android application, and sensors such as temperature and soil moisture sensors. The method allows farmers to automate irrigation, offers a manual override option for extra control, and saves time and money [24]. Automation of agricultural machinery for soil sterilization before sowing is proposed in [25]. It is integrated into the IoT infrastructure to monitor soil factors including temperature, pH, and moisture, as well as the amount of disinfectant applied to the ground. Using the acquired system, it is possible to measure plant protection products administered. Automation management has brought about significant advancements in the agriculture industry. It allows farmers to monitor their operations remotely, optimize crop yield, reduce costs, and improve sustainability. With the help of IoT devices and data analytics, farmers can make more informed decisions, leading to more efficient and profitable farming practices.

### *C. Deep Learning based Image Processing approach for Agri 4.0*

Image processing is one of the essential aspects of Deep Learning (DL). It involves analyzing and modifying images to extract relevant information that can be used for a variety of applications, including object recognition, image classification, and segmentation. In DL, convolutional neural networks (CNNs) have been shown to be effective in image processing. CNNs extract high-level features from input images by using multiple layers of filters. These features are then used to classify or segment the image. The ability of DL models to learn from and adapt to new data makes them an ideal solution for image processing tasks, as they can constantly improve their accuracy and performance.

As DL models continue to develop, they will undoubtedly become more significant in the field of image processing. In the context of Agri 4.0, DL-based image processing techniques are gaining prominence for analyzing and interpreting agricultural imagery. By training a DL algorithm on a large dataset of labelled images, patterns and features can be automatically extracted from images. These insights can then be used to make informed decisions about agricultural challenges such as detecting plant diseases, pests, and weeds and these technological approaches are also being used to predicting the crop yields and to grade agricultural products in a transparent manner.

#### **Plant Disease and Pest detection:**

Crop disease and pest detection are imperative for a number of reasons. Early detection of crop damage can assist farmers in taking precautionary measures to prevent the spread of diseases or pests and protect their harvests. This may result in higher crop yields and lower crop losses. Furthermore, early detection of crop damage can aid in the prevention of disease and pest spread to other crops or surrounding ecosystems. The use of DL-based image processing technology for crop disease and pest detection is becoming increasingly common. These technologies can provide farmers with a more accurate and timely way to identify crop damage, protect their crops, and reduce crop losses.

The authors [26] used a convolutional neural network (CNN) to classify images of diseased and healthy leaves. They optimized the hyperparameters of well-known pre-trained CNN models such as DenseNet-121, ResNet-50, VGG-16, and Inception V4. The studies were carried out using the PlantVillage dataset, which contains 54,305 picture samples of various plant disease types classified into 38 subcategories. Classification accuracy, sensitivity, specificity, and the F1 score were primarily utilized to assess the model's performance. The experiments showed that DenseNet-121 achieved a classification accuracy of 99.81%. This is a significant improvement over previous approaches to leaf disease detection.

The rapid development of unmanned aerial vehicles (UAVs) and hyperspectral imaging technology has the potential to revolutionize plant disease detection. UAV-borne hyperspectral remote sensing (HRS) systems can acquire high-resolution spectral data of plants. This data can be used

to train deep learning models for plant disease detection. Deep learning models have been shown to be more accurate than traditional machine learning algorithms for plant disease detection [27]. However, there are still some challenges and limitations in this area, such as the need for large and high-quality datasets, the high cost of UAV-borne HRS systems, and the difficulty of generalizing deep learning models to new environments. These advancements highlight the viability of further research while also addressing potential problems and limitations in this field.

DL-based computer vision techniques are being used to develop automated systems for plant disease diagnosis. A CNN model was developed to classify rice and potato leaf diseases [28]. The CNN model was trained on a dataset of 5932 rice leaf images and 1500 potato leaf images. The model was able to classify rice images with 99.58% accuracy and potato leaves with 97.66% accuracy. These results demonstrate that the model can be used to develop highly accurate and reliable plant disease diagnosis systems.

VGG-ICNN is a lightweight convolutional neural network (CNN) model developed for the identification of crop diseases using plant-leaf images. The model consists of around 6 million parameters, which is substantially fewer than most of the available high-performing deep learning models. VGG-ICNN was evaluated on five different public datasets covering a large number of crop varieties. The model achieved an accuracy of 99.16% on the PlantVillage dataset, which is a dataset of plant-leaf images with 38 different types of diseases [29].

Grape leaf diseases such as black measles, black rot, and leaf blight can be diagnosed using multiclass support vector machine (SVM) and image processing. The authors [30] use K-means clustering to automatically separate the area of disease symptoms from the healthy parts of the leaf. Features are then extracted from the disease area in three color models: RGB, HSV, and  $I^a \cdot b$ . SVM is used for classification, with principal component analysis (PCA) performed for feature dimension reduction. The proposed method was compared with two DL methods, namely CNN and GoogleNet, and achieved a classification accuracy of 98.97%. The processing time for the proposed method was significantly shorter than those of the DL models.

DL-based approach [31] that employs the techniques of computer vision and image processing was used to develop a system for the automatic detection and classification of paddy plant diseases. The system was trained on a dataset of images of diseased and healthy paddy plants. After image pre-processing, image segmentation was used to determine the diseased section of the paddy plant. The diseases were then identified using an SVM classifier and CNNs. The system achieved a validation accuracy of 0.9145. The system can be used to help farmers identify and treat paddy plant diseases, which can improve crop yields and reduce crop losses.

The authors of [32] discuss the development of a deep learning model for the detection and classification of chickpea diseases. The model used a dataset of 8,391 images of chickpea plants, some of which were diseased. They used

a combination of CNNs and long short-term memory (LSTM) networks to extract features from the images and classify the diseases. The CNNs were used to extract features from the images, while the LSTMs were used to classify the diseases based on the extracted features. The model achieved an accuracy of 92.55%, which is higher than the accuracy of other methods that have been used for chickpea disease detection.

A two-stage deep learning-based approach was developed to identify and segment corn disease lesions and estimate their severity under complex field conditions [33]. A custom dataset of handheld images of corn leaves infected with Gray Leaf Spot, Northern Leaf Blight, and Northern Leaf Spot diseases was used to train three semantic segmentation models using SegNet, UNet, and DeepLabV3+ network architectures. The UNet model was best for stage one, achieving up to 0.9422 mean weighted intersection over union (mIoU) and 0.8063 mean boundary F1-score (mBFScore). The DeepLabV3+ model was best for stage two, identifying disease lesions with a mIoU of 0.7379 and mBFScore of 0.5351. In the test set, an R2 value of 0.96 was achieved, which denotes that the integrated (UNet-DeepLabV3+) model predicted the severity of three diseases very close to the actual observations.

The author of [34] proposes a new deep learning architecture for multi-crop disease detection called the Complete Concatenated Deep Learning (CCDL) architecture. The CCDL architecture is composed of a series of Complete Concatenated Blocks (CCBs), each of which consists of a point convolution layer followed by a complete concatenation path. The point convolution layer helps to reduce the number of parameters in the model, while the complete concatenation path helps to improve the utilization of feature maps. The CCDL architecture is trained using the reorganized Plant Village dataset. The trained model is then pruned to reduce its size. The pruned model is called the Pruned Complete Concatenated Deep Learning model (PCCDL), and achieves a higher classification accuracy of 98.14% than other state-of-the-art models. The PCCDL model also has a smaller model size, which makes it more efficient to deploy in real-world applications.

### **Weed Detection:**

Weeds that compete for sunlight, nutrients, water, and space with crops. Uncontrolled weed growth can cause significant economic and ecological losses. Weed detection is a critical task in Agri 4.0, as it allows for the targeted application of herbicides and other weed control measures. In recent years, there has been a growing interest in using image processing-based deep learning (DL) techniques for weed detection. DL models can be trained to identify weeds in images with high accuracy, and this information can be used to guide targeted herbicide applications. This strategy has the potential to lessen the environmental effect of herbicide use while increasing agricultural yields.

CNNs can be used to effectively detect weeds in Chinese cabbage fields using UAV imagery [35]. In this study, CNNs were trained on a dataset of UAV images that had been pre-processed and segmented into crop, soil, and weed classes.

The overall accuracy of the CNN was 92.41%, which was considerably higher than the accuracy of the random forest classifier (86.18%). These results suggest that CNNs can be used to effectively detect weeds in Chinese cabbage fields using UAV imagery.

The study [36] examines the usage of a single-stage object detection You Only Look Once (YOLO) v5s CNN model trained on photos of five different plant species: sugarcane, banana trees, spinach, pepper, and weeds. To automatically classify crops and weeds, the model was trained on UAV imagery. The outcomes showed that increasing the number of training epochs from 100 to 600 improved the classifier's performance. However, when the number of epochs was extended to 700, there was a tiny decrease. The optimum outcome was obtained after 600 epochs, with a classification accuracy of 67%, weed precision of 78%, and weed recall of 34%. The results indicate that the training epoch of YOLO v5s has a substantial impact on the model's resilience in autonomous crop and weed classification.

### **Transparent Grading:**

Transparent grading is a critical component of Agri 4.0, as it allows farmers to make informed decisions about the quality and value of their crops. Traditional grading methods are often time-consuming, labor-intensive, and subjective. Image processing-based approaches using deep learning techniques offer a promising alternative, as they can be used to automate the grading process and provide more objective and accurate results. A DL-based image processing approach can automate the grading process transparently. Compared to conventional grading techniques, such an approach is more precise and efficient. The extracted features from agricultural product images can then be used to train a DL model to identify and classify different features of agricultural products, such as size, color, and shape. The products can then be rated based on their value and quality using the information provided. Image processing-based approaches using deep learning techniques can revolutionize transparent grading in Agri 4.0 by making the grading process more efficient, accurate, and objective. This can benefit farmers by helping them to improve the quality of their products, increase their yields, and reduce their costs. It can also benefit consumers by providing them with more information about the products that they are purchasing.

### **The benefits of transparent grading include:**

**Precision and efficiency:** Transparent grading is more precise and efficient than conventional grading techniques. This is because it can be completed considerably more quickly and is less susceptible to human error.

**Better quality control:** By ensuring that items are rated correctly, transparent grading can assist farmers in improving the quality of their output. Farmers may earn more money as a result of this.

**Improved transparency:** Transparency can be increased by using transparent grading, which can also help make the agricultural supply chain more transparent. This can help consumers by giving them with additional information on the products that they are purchasing.

By giving farmers a more precise, effective, and transparent means to grade their products, such an approach has the potential to transform the agricultural sector.

A fruit identification and grading system uses a CNNs to extract features from fruit images. The features are then used to classify the fruits and to grade their quality. The system was evaluated on a dataset of fruit images, and it achieved an accuracy of 98% in fruit identification and 95% in fruit grading. This system [37] is a promising approach for automated fruit grading, and it has the potential to be used by farmers to improve the quality and profitability of their produce. The authors proposed [38] a DL-based approach for automated mango grading. The method employs a CNNs to extract features from mango images, which are then used to classify the mangoes into three quality categories: fit, average, and good. The system underwent evaluation on a dataset of mango images from three different types, and it obtained an accuracy of 93.23% for variety detection and 95.11% for quality grading. The proposed technique is a major advance over the old manual grading approach and has the potential to change the mango grading industry.

A novel method for automatic classification and grading of multiple varieties of apple fruit is proposed [39]. The method uses image segmentation, feature extraction, and classification to achieve high accuracy for fresh and rotten apples. The method was evaluated on six different varieties of apples, and it achieved an average accuracy of 95.27%. The proposed method is a promising new approach for automatic classification and grading of multiple varieties of apple fruit. A machine vision system for grading fruits was developed using DL techniques [40]. It was trained on two data sets (apples and bananas) and achieved an average accuracy of 99.2% and 98.6%, respectively. The system was tested on actual samples in real time, with an accuracy of 96.7% for apples and 93.8% for bananas. The system is a promising new tool for automating the visual inspection of fruits. It is non-destructive and cost-effective, and it can be used to grade fruits in real time.

A non-invasive automated system for grading bananas based on their quality and size was proposed in [41]. The system uses a combination of RGB and hyperspectral imaging to extract features from the bananas, which are then fed into a deep learning model for classification. The model achieved an overall accuracy of over 98%, which is higher than other methods that have been reported in the literature. The system is fast and can be used in real-world farm postharvest processes. A dual-channel system using the DL technique of CNNs was developed for banana grading. The system uses RGB and hyperspectral imaging to classify bananas by size and perspective [42]. The CNNs was trained on a dataset of 10,000 banana images and achieved an accuracy of 98.4% and an F1-score of 0.97. The system can be used to automate the grading of bananas on assembly lines, which can improve production rates and reduce costs. The system can also be used to classify other types of fruits and vegetables. These methods, which are comparable to state-of-the-art techniques, have the potential to significantly improve the efficiency and accuracy of agro-product grading. This can



lead to reduced costs and improved quality for the transparent grading system in the agriculture industry.

#### CONCLUSION

This article highlights the potential of IoT and DL for sustainable farming in the developing Industry 4.0 era. The use of these technologies can lead to more efficient use of resources and increased productivity while reducing the environmental impact of agriculture. IoT enables automation, which shows the path to tackle the unavailability of the workforce and also helps timely intervened approach in order to monitor the environmental surroundings in the farming land. DL techniques enable the detection of diseases that occur in leaves, plants, etc., and this will help farmers make more informed decisions about preventing the spread of diseases among crops. The application of this technology can also lead to the creation of more precise predictive models and improved resource management. However, challenges related to data privacy, security, and interoperability, as well as the cost and complexity of implementation, need to be addressed.

Agri 4.0 practices have the potential to promote sustainable agriculture. Careful planning, investment, and collaboration among farmers, public-private partnerships, policymakers, and technology providers will be crucial in realizing the benefits of these technologies. Further research is necessary to explore the potential of these technologies and focus on facing the challenges that lie ahead.

#### ACKNOWLEDGMENT

The authors express their gratitude for the reviewers and editors useful comments on how to improve the manuscript. The authors acknowledge their institution.

#### CONFLICT OF INTEREST

The authors state that they have no conflict of interest.

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